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Application of Artificial Intelligence in Spacecraft Ground Testing

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Abstract. With the accelerated application of new-generation information technologies, developed countries have implemented digitalization strategies to gain a competitive advantage in the digital era. Artificial intelligence (AI) is widely used in a wide range of modern industries. Our country has put increasing emphasis on AI technologies, and our aerospace industry is being more digitalized. This study focuses on the application prospects of AI in spacecraft ground testing. It aims to build smart labs driven by products and discusses how to integrate AI into the process of quality supervision, instability prediction, situational awareness analysis for equipment, and optimization of knowledge-driven product design, thus digitalizing spacecraft ground tests.

1. Introduction

Ground testing is a key link in evaluating and validating the functions, performance, and reliability of a spacecraft [1] and ensures a successful launch. Ground tests often involve a large amount of equipment and considerable preparation efforts. They are also time-consuming and difficult to manage. Artificial intelligence (AI) is the study and development of intelligence that simulates and expands human intelligence [2]. Computer science, control theory, information theory, mathematics, and other disciplines contribute to its development. As the internet, computer technology, and algorithms have evolved, a significant improvement has been observed in the performance of AI in deep learning [3]. Speech recognition, fuzzy recognition, and image recognition are some of AI's applications now. Applying AI in spacecraft ground testing would address existing problems in the test models, improve quality reliability and test safety, while facilitating product design based on AI-powered test data analysis and optimizing the design process.

2. Demand Analysis

As part of the initiative to "digitalize the aerospace industry, develop digital spacecraft, and drive digitalized research and development, management, and coordinated industrial development" in China, accelerating the digitalization transformation and deepening the integration between digitalization technologies and spacecraft development have become key goals for future development. Currently, the industry is focusing on the development of a model-based digital coordinated research and development system. However, relevant digitalization efforts have just began in the R&D of spacecrafts. While a variety of professional models have

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been developed in mechanics, information management, and energy management, they are relatively independent from one another. A unified model that supports collaborative innovation throughout the entire product lifecycle has not been created.

Ground testing, a key link in the R&D of spacecrafts, still relies heavily on experiments, which involve many manual processes, leaving room for improvement in both production efficiency and quality consistency. The development of a model-based digital and intelligent test platform can significantly improve production efficiency, test quality management, and safety management, merge product development with testing processes, and facilitate the creation of a unified model.

3. Smart Test Procedures and System

Based on the degree to which advanced information technologies and ground testing methods have been integrated, there are four development stages for the test system, i.e., automatic testing, digital testing, network-based testing, and smart testing system [4]. From a conventional model dominated by physical experiments, the system gradually evolves into one that iterates and transmits data, and processes the data as knowledge.

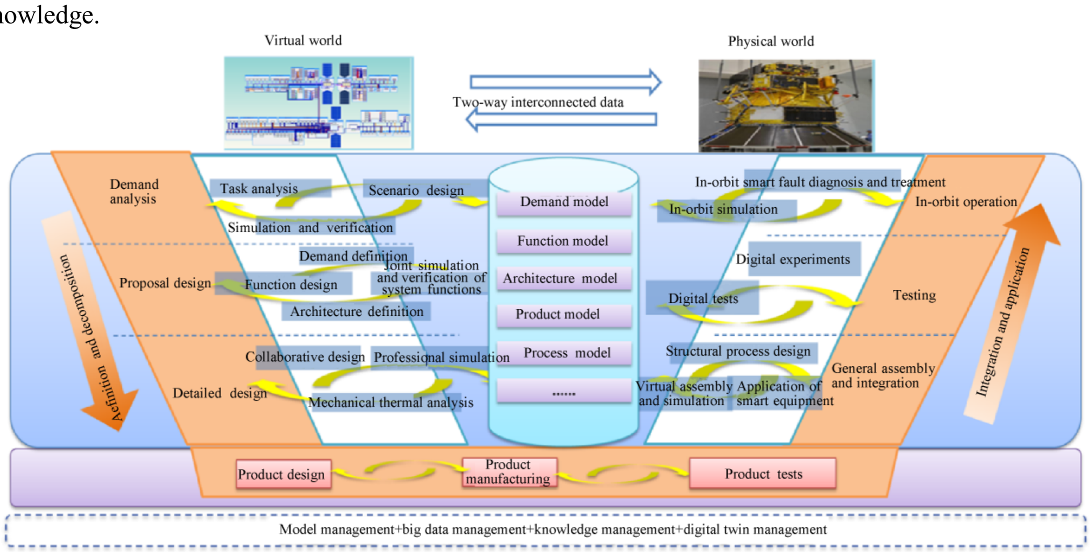

Figure 1. Block diagram of a model-based digital testing and collaborative R&D system（Digital CAST）.

To redesign the test procedure and create a smart test process management system, we divide the system into four parts, i.e., a test design system, a test control system, a test process management system, and a test evaluation system.

The test design system is mainly driven by a digitalized R&D model. It simulates the in-orbit conditions and generates a ground testing model, based on which a comprehensive ground testing plan covering optical, mechanical, electrical, and thermal dimensions can be developed for either virtual simulation tests or physical experiments at the processing end.

The test control system translates the preliminary model generated by the design system into in-orbit environmental conditions to realize the control of test procedures without manual intervention.

The test evaluation system compares the results of virtual tests with conventional physical experiments to correct the design model and accumulate test data for use in subsequent test systems through autonomous learning.

The test process management system combines the design, control, and evaluation systems using a digitalized structure. It then exports the model for downstream processing and facilitates a dynamic data flow.

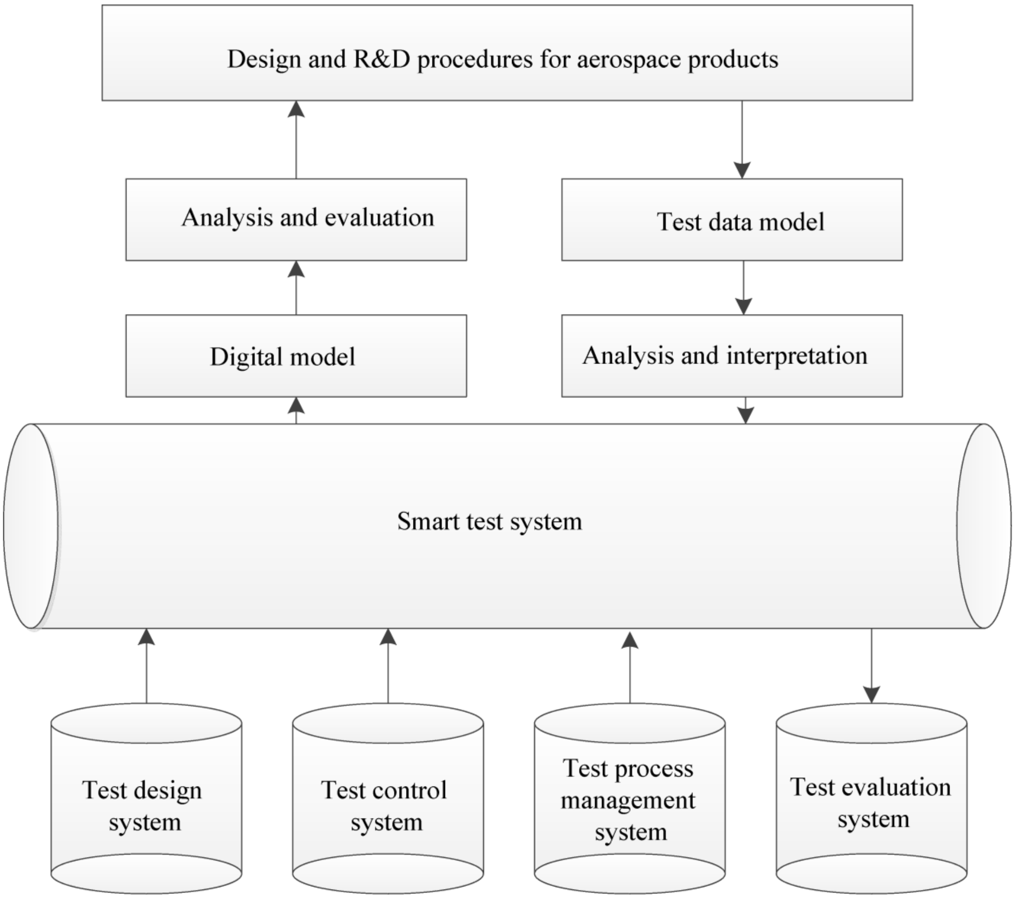

Figure 2. A smart test system.

4. Application of AI in Quality Control

In the current testing process of aerospace products, quality management is primarily accomplished through the use of tables. Although the approach can cover the entire testing process, it involves a considerable amount of manual work and recognition. The majority of recorded data is not digitalized or automated. As a result, most quality control records are in the form of paper documents instead of electronic ones, falling far short of the goal of digitization.

By combining the elements of process control in test quality management with technologies like image recognition and fuzzy recognition, we are able to obtain information such as process management parameters and test data in a fast and effective manner, and digitalize quality control. Using a digital quality control model, we can effectively solve the problems associated with traditional paper table filing, such as low efficiency, cumbersome documentation, and difficult tracking. Meanwhile, we can perform failure mode analysis and potential failure analysis during product testing. Using a smart prediction technology, we are able to diagnose potential quality hazards and generate quality risk alerts. With such an approach, we can upgrade process quality management and control to quality risk prediction, thus validating the reliability of the product and improving its quality. Digital process quality control allows us to compare product models horizontally and vertically.

5. Smart Test Safety Predictions

Safety management of the test process is essential for the process management of spacecraft ground testing. Safety management based on safety systems is a concept developed from safety system engineering. According to the *Guidance for Identification of Spaceflight Industrial Hazard Installations* (QJ 3299A-2008), by analyzing hazard installations during the ground testing process for spacecrafts, the relevant hazard installations can be determined.

Safety system engineering divides any safety management practice into three parts, namely, human, machine, and loop [5]. On such basis, the traditional approach to hazard installation identification breaks down each hazard installation into three parts and performs a SHEL analysis, forming the fundamental safety logic. By combining the test process with smart safety patrol units, a dynamic monitoring system that integrates mechanical vision, infrared imaging, acoustic wave analysis, gas detection, situational awareness analysis is developed. The human-machine-loop situation can be predicted, and the safety management pattern is upgraded, thus enabling smart safety predictions and addressing safety issues during the test.

6. Knowledge-driven Optimization of Product Design

As information-powered production characterized by digitalization, virtuality, collaboration, integration, and intelligence is developing [6], knowledge-driven design has become a trend in spacecraft research and development. Such knowledge is built up from spacecraft R&D standards, previous performance data and parameters, innovative patents, design specifications, and process control methods, making it an essential element in designing spacecraft.

Instead of working together holistically, each stage of the spacecraft design process is relatively independent. A whole-process R&D system is not in place. As a consequence, the analysis and processing of test data has not directly benefited product design at present [7-9].

A knowledge-driven approach to product design and optimization, on the other hand, seeks to create interactions between test data and product design. Unlike the traditional method, each model will be designed using test data as the basis and core.

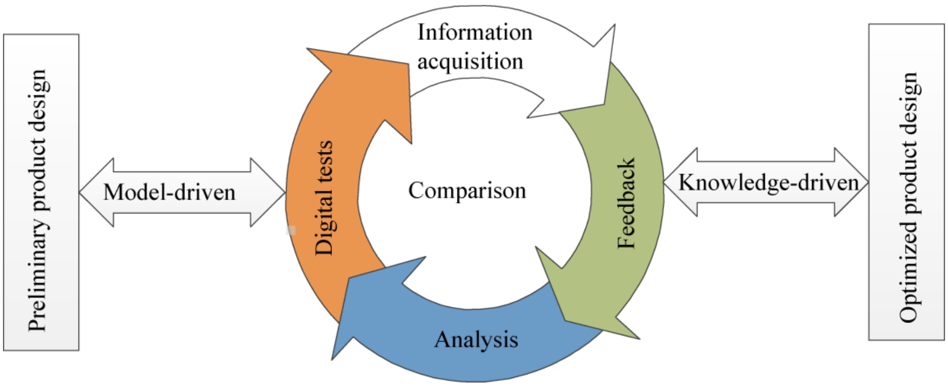

Figure 3. Optimized product design driven by test knowledge.

Test data are compared with parameters of the designed model in an intelligent manner by the test evaluation system. Multidimensional elements are identified, such as performance parameters, temperature, mechanical properties, and external environmental parameters, and they are compared with design indicators. Through simulation and redesign, an optimized product design will be generated. This approach can maximize system functions and optimize the product design, as well as facilitate the improvement of management throughout design, processing, production, and acceptance check.

7. Conclusions

By integrating AI in spacecraft ground testing, we can satisfy the long-term demand for spacecraft digital development and digital collaboration, improve the test procedures and quality management, and realize early perception and prediction of instability factors that may affect equipment safety. Thus, the topic is of significant research value. Presently, fully leveraging AI can facilitate the digital transformation of spacecraft.

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